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PERSPECTIVES

# AI-Driven Decision Support Framework for Preventing Medical Equipment Failure and Enhancing Patient Safety: A New Perspective

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**Abstract:** Medical equipment failures pose serious risks to patient safety and healthcare system efficiency. Although AI-based predictive maintenance (PdM) has shown promise in other industries, its application in healthcare remains fragmented and insufficiently aligned with human-centered principles. This perspective paper proposes a novel AI-driven decision support framework that integrates systems thinking and prioritizes human-centered design. By leveraging real-time sensor data and historical maintenance records, the framework proactively predicts equipment failures and reduces downtime. It incorporates insights from key stakeholders, including biomedical engineers, technicians, patients, and administrators, to ensure human-centered and ethically responsible implementation. The paper also addresses major challenges such as data integration, human factors, and organizational readiness, offering practical strategies for sustainable adoption. This work contributes to the evolving role of AI in healthcare by emphasizing empathy, stakeholder collaboration, and safety, ultimately promoting more reliable medical devices and improved patient outcomes.

**Keywords:** artificial intelligence, equipment failure analysis, maintenance, predictive, patient safety, human factors, clinical decision support systems

## Introduction

The reliability of medical equipment is essential for effective patient care. However, despite ongoing maintenance efforts, unexpected malfunctions still occur, posing risks to patient safety and leading to increased operational costs.[1] Failures range from minor issues to critical breakdowns, particularly in high-dependency settings like ICUs. A key challenge is the absence of integrated, data-driven systems to track and predict equipment performance, leading to inefficiencies in failure detection and prevention.[2] Such errors emphasize the need for novel solutions to address the issue of medical device failures in healthcare settings.

Artificial intelligence (AI) can offer promising solutions to the problem of medical equipment failure as it can be extremely useful in forecasting, detecting, and preventing errors.[3] AI algorithms have the ability to detect possible failure trends by evaluating massive volumes of data collected from equipment sensors and maintenance records. This proactive method enables prompt interventions, lowering the chances of equipment failure and enhancing patient safety.

Implementing AI in healthcare does not entirely rely on accessing and analyzing existing patterns in the raw datasets, it requires a structured framework to address the complexities of AI technology and the healthcare industry.[4]

The diversity of stakeholder competencies in the healthcare industry creates limitations in the performance of the developed AI system. Each group brings distinct backgrounds, priorities, and expectations, creating conflicting requirements and inconsistent adoption practices which may limit the performance and usability of AI-driven solutions if not



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carefully addressed during the design and implementation step. Having a structured framework can provide an innovative approach to address these complexities and limitations. The human-centered design and systems thinking principles in the framework ensurethat diverse stakeholder needs are identified, balanced, and incorporated early in the process. Meanwhile, it is very effective to ensure access to relevant information and facilitate its flow by creating clear channels and processes for gathering and sharing real-time data from different sources. In addition, establishing a smooth and structured method for information exchange and a feedback loop between AI experts and end-users can greatly influence the process.

Furthermore, integrating AI into healthcare equipment management involves developing a modular decision support framework composed of data collection layers (equipment sensors), AI models such as Random Forest, Support Vector Machines (SVM), and interfaces tailored to various healthcare environments. These frameworks use AI algorithms, such as ensemble methods, to analyze large volumes of real-time sensor data and historical maintenance logs, enabling early detection of anomalies and prediction of equipment failure in clinical settings.[5] The use of AI in this scenario is particularly appropriate because of its capacity to handle complex datasets and learn from existing patterns. Unlike traditional maintenance methods that depend on scheduled inspections or reactive repairs, AI-driven systems continuously monitor equipment performance in real-time, allowing for predictive maintenance (PdM) strategies. This proactive strategy reduces downtime, decreases maintenance costs, and ensures equipment availability by enabling early fault detection through real-time data analysis and predictive modeling.

In recent years, a variety of AI tools have been developed across different contexts, with promising results in preventing and mitigating medical equipment failures, thereby improving maintenance management effectiveness.[6,7] Table 1 provides an overview of recent research on AI-driven approaches for predicting and preventing medical device failures. It highlights key advancements, identifies opportunities for improvement, and suggests strategies to overcome existing challenges.

Several studies have investigated the use of AI to forecast and prevent equipment failure in healthcare settings. For instance, Machine Learning (ML) algorithms are used to prioritize preventive maintenance, with the goal of ensuring prompt reactions to possible breakdowns.[17] By utilizing real industrial data, the study by Rojek et al[17] emphasizes the cost-effectiveness of AI solutions that can be tailored to enterprises of all sizes. Similarly, Shamayleh et al[11] describe a PdM approach that uses Internet of Things (IoT) and ML to detect and predict significant equipment breakdowns in healthcare facilities. Economic investigation shows significant cost savings, with promising improvements to maintenance methods.

The integration of PdM technologies into healthcare management is also critical for guaranteeing medical device reliability and optimizing maintenance plans. Studies such as Abd Rahman et al,[8] describe predictive models designed specifically for medical equipment failure prediction, allowing for more extensive maintenance planning and budget allocation. Ensemble classifiers emerge as effective solutions for improving maintenance procedures and lowering expenses. However, challenges such as restricted sensor data availability and reliance on existing data highlight the importance of further studies to increase model accuracy and reliability.

Studies have also focused on forecasting failures in specific medical equipment that are crucial to patient care. For example, Wang et al[9] created an ML model to predict noninvasive ventilation (NIV) failure in ICU patients, allowing for early intervention and monitoring. Similarly, Badnjević et al[12] used ML to accurately forecast defibrillator performance, demonstrating the effectiveness of AI in analyzing medical device performance.

The selected articles differ in subject matter, approach, or both. More than half of these studies focused on the PdM of specific medical devices such as clinical laboratory analyzers, imaging devices, defibrillators, and infant incubators. Others discussed PdM for medical equipment in general, or maintenance management strategies across many facilities. The literature review indicates that implementing a PdM program reduces unnecessary service visits, enabling engineers to optimize their time and efficiency. Furthermore, automated device health monitoring provides greater visibility into device conditions and operations. PdM is also expected to save resources as it can replace medical device parts only when they are needed, as opposed to preventive maintenance, which means frequent part replacement. This approach contributes to more efficient resource management in hospitals.

**Table 1** Recent Research About the Role of AI in Preventing Equipment Failure

| Year | Purpose | Approach/ Methodology | Results | Gap/Limitations | Relevance to Proposed Framework | Framework Contribution |
|---|---|---|---|---|---|---|
| A. Medical Equipment in Healthcare Settings | | | | | | |
| 2023[8] | Predict medical device failure for healthcare optimization | Predictive ML model classifiers with SGDM optimizer trained using 15 Malaysian facilities, | 79.5% accuracy, optimized maintenance, annual savings (MYR 326K/year), ML outperforms DL in accuracy | Excludes unstructured data; may miss failure events | Supports real-time predictive maintenance, but lacks human-centered design. | Stakeholder-informed implementation |
| 2022[9] | Predict non-invasive ventilation (NIV) failure post-extubation | ML with feature elimination and hyperparameter tuning in ICUs | NIV failure rate: 26.7%. Identified 15 key features, predicts early failure within 6 hours | Limited external validation and potential bias from retrospective data | Real-time risk prediction models in ICUs | Embedding design thinking and multidisciplinary user engagement for actionable insights |
| 2020[10] | Nanotech-based IV monitoring system to detect infusion failure | Fuzzy logic-based IV nanotech monitoring system with pressure, pH, and $O_2$ sensors | Automated failure detection in infusion systems to alert nurses | Not reported | Introduces automated detection and reinforces sensor-based monitoring | Extending to AI-integrated alerting mechanisms |
| 2020[11] | IoT-ML framework for PdM of critical equipment | 10-step PdM workflow using SVM, fault logs, and feasibility evaluation | 25% cost savings, scalable for medical equipment, SVM: 96.1% accuracy | Hardware dependency and system integration challenges | Scalable for medical equipment with strong and scalable technical workflow | Embedding organizational context and ethical, user-centered deployment strategies |
| 2019[12] | Predict defibrillators performance | Feature selection (InfoGain, DT, Wrapper) and classification (DT, RF, KNN, SVM) | RF accuracy: 99.6% | Limited to specific device dataset | Demonstrates high accuracy and prediction performance but limited in system-wide applicability and stakeholder involvement | Broad relevance via co-designed processes |
| 2017[13] | Predicting failure of imaging devices | SVM-based feature extraction to predict PHILIPS iXR component failure | Enhanced customer satisfaction, cost savings, and reduced downtime | Rare failure scenarios are not included | Focuses on predictive modeling of specific imaging devices. | Addressing rare-event modeling, incorporating empathy and system-wide design across multiple device types |
| 2019[14] | Estimate the performance of infant incubators | ML classifiers (80/20 split) with NB, DT, RF, KNN, and SVM | DT: 98.5% accuracy, 95% sensitivity, and 100% specificity | Limited to incubators but findings are generalizable to other devices | Strong classification performance in specific devices, contributes to our domain generalizability | Scalable, user-centered framework applicable for various healthcare settings |

(*Continued*)


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**Table 1** (Continued).

| Year | Purpose | Approach/ Methodology | Results | Gap/Limitations | Relevance to Proposed Framework | Framework Contribution |
|---|---|---|---|---|---|---|
| 2020[15] | Expert maintenance prediction for incubators | ANN and FL classifiers for device performance prediction | 100% accuracy on 137 inspection samples | Not reported | Uses hybrid AI methods effectively, supports our multi-model integration design | Embedding ethical considerations and real-world usability through cross-stakeholder integration |
| 2019[16] | Prediction of medical specimen analyzers failure | SPC with data mining and KNN for prediction | 94% prediction accuracy | Limited validation for diverse clinical settings | Validates data-driven prediction for lab devices | Emphasis on human-centered validation and readiness for deployment in actual clinical workflows |
| B. Industrial Applications Relevant to Medical Context | | | | | | |
| 2023[17] | Optimize equipment maintenance using AI | Computational analysis with ML/AI on industrial data for predictive maintenance | Effective with annotated data, improved efficiency at low cost | Lack of annotated data, limited applicability across systems | Addresses data challenges and scalability in industrial AI implementation | Data integration, empathy, and system-wide collaboration |
| 2021[18] | ML applied to online data for insights and tools in maintenance | Multi-class ML on Microsoft dataset with holdout validation | Addressed class imbalance and proposed better feature handling | Feature complexity and data imbalance persists | Framework leverages improved preprocessing and model tuning for healthcare reliability but lacks alignment with patient safety and system readiness | Comprehensive, human-aware PdM strategy |
| 2019[19] | Failure prediction in industrial ovens | SVM for classification and RNN-LSTM for 5-tier failure prediction | SVM: 85% accuracy, 76% precision, F1-score: 86% | Generalizable results to various equipment and environments | Shows value of time-series and hybrid modeling | Tailor the method to healthcare complexities through ethical and user-informed design |


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Despite work reported in several studies, significant challenges remain in the use of AI to prevent medical device failure. Key issues include class imbalance, limited sensor data availability, and applicability across diverse production profiles. To address these challenges and enhance the effectiveness of AI-driven initiatives, several strategies can be proposed. First, improving data collection is important as AI models rely on diverse and extensive datasets for improved model accuracy and generalizability. Additionally, future research should focus on advanced feature engineering, developing improved feature selection and learning algorithms to enhance prediction accuracy. Moreover, integrating AI with IoT technology can enable real-time data collection and analysis, accelerating predictive maintenance tasks. Finally, interdisciplinary collaboration among healthcare experts, data scientists, and engineers is crucial to develop AI solutions tailored to the specific needs and challenges of healthcare environments.

## AI-Driven Framework Development

Designing and developing an AI-based framework to address equipment failure issues extends beyond enhancing device functionality, performance, durability, safety, and effectiveness. This framework is heavily influenced by factors related to the human interaction with equipment, the human-equipment interface, and the environment in which this interaction takes place. It is therefore important to adopt a systems approach[20] that integrates the human perspective (Figure 1A), design considerations (Figure 1B), system-level factors (Figure 1C), and potential risks (Figure 1D).

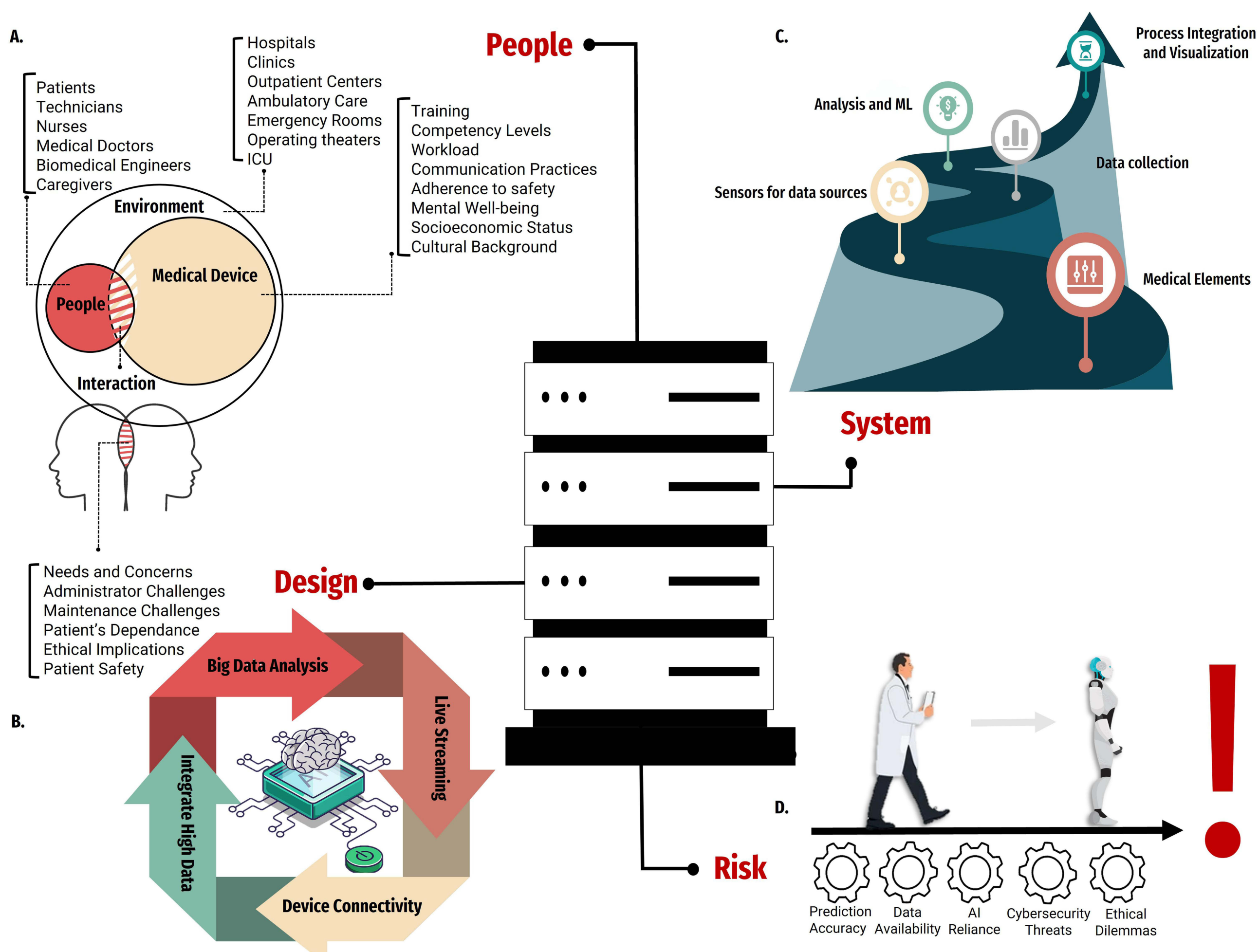


**Figure 1** Graphical illustration of the AI framework developed using a modified system thinking approach. The framework incorporates key elements and summary findings of (**A**) people, (**B**) design, (**C**) system, and (**D**) risks encountered throughout framework implementation.

## People Perspective

First, a comprehensive and well-designed framework must incorporate the human factor into the equipment's components, firmware, and user interface.[21] Understanding the human factors involved in medical equipment maintenance is a complex and dynamic process. It depends on who is interacting with the equipment, their interactions with the environment, how they are affected by equipment errors, wear and tear, and how information is perceived and processed.

In parallel with human factor considerations, the AI component of the framework involves both supervised and unsupervised learning strategies. Supervised models such as Random Forest, SVM, and Gradient Boosting are trained using labeled equipment failure data to classify the risk of malfunction. These models rely on input features derived from sensor telemetry, usage history, and prior maintenance records. Additionally, unsupervised learning approaches like clustering and anomaly detection are used to flag unexpected patterns or rare failure events not captured during training. This hybrid approach enhances predictive accuracy and enables early alerts to trigger maintenance actions.

The "human" aspect of equipment use includes both patients (end-users) and healthcare providers (such as technicians, biomedical engineers, nurses, caregivers, therapists, pharmacists, and doctors).[22] Each group contributes distinct perspectives, challenges, and insights to the design of the AI framework. The experiences, needs, and conditions of patients form the core focus of the framework. Patients introduce several important factors, including their clinical and physical conditions, their personal data, as well as social, emotional, and psychological dimensions.[5] Patients with complex or critical medical conditions, or those with physical disabilities, often require more frequent use of equipment, which may result in a higher incidence of device malfunctions and a need for more frequent maintenance.

Additionally, variations and inaccuracies in patient data may require equipment settings to be adjusted or calibrated.[23] Analyzing human factors can enable proactive maintenance predictions for each piece of equipment through AI-driven analytics. Examples of such factors include patient profiles, the number of patients, the type and frequency of equipment used. Similarly, some other factors can also be considered, including socioeconomic status, cultural background, and mental well-being, which also significantly influence the patient-equipment experience and outcomes. Furthermore, individual preferences, fears, and anxieties can strongly impact interactions with medical equipment and treatment regimens. For example, a patient with claustrophobia who has heard about incidents involving Magnetic Resonance Imaging (MRI) machines may be reluctant to undergo an MRI scan, affecting both the frequency of equipment usage and the effectiveness of treatment. Similarly, patients who are aware of past incidents involving certain imaging machines at specific hospitals may be hesitant to use them, further impacting patient safety and operational efficiency.

Healthcare providers constitute a set of expertise, skills, and insights that are essential in delivering quality care where they can influence and be influenced by patient factors. Their physical and psychological well-being, cognitive abilities, and level of expertise all impact on their interactions with patients and medical equipment. Considering a scenario in which a healthcare provider is stressed or experiencing burnout, the ability to communicate effectively with patients, safely operate a medical device, and make sound clinical decisions can be significantly affected. Reduced attention can also increase the likelihood of accidents or malfunctions in the equipment and might put the patient's health at risk. Other factors related to cognitive abilities like attention, memory, and problem-solving skills, play a crucial role in the accurate and efficient use of medical equipment. Whether it is interpreting diagnostic results, calibrating complex machinery, or troubleshooting technical issues, these factors interrupt the effective use of medical equipment and increase wear and tear rates.

Identifying the system's location involves determining the physical settings where human-equipment interactions occur. A robust framework for preventing equipment failure must account for the wide range of environments in which human-equipment interactions occur, including hospitals, clinics, outpatient centers, and ambulatory care settings, while also integrating data sources, an analytics platform, and a user-friendly interface.

Each environment presents unique challenges and considerations that can impact equipment performance and reliability. For instance, medical equipment in hospitals can be used in different departments like emergency rooms, operating theaters (OT), and ICU. These settings can vary in terms of patient care protocols, staff experience levels, and environmental conditions, which influence equipment usage and maintenance requirements. Moreover, the geographic location of a facility affects equipment management, for example, facilities located in regions with extreme weather conditions or natural disasters will face additional maintenance challenges. In addition, the facility size, layout, and infrastructure support systems must be considered in designing a framework as they affect equipment maintenance frequency.

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Several human-related factors can impact equipment functionality, maintenance, and safety, as the actions, behaviors, and interactions can greatly influence equipment operation and maintenance. These factors include user training, competency levels, workload, communication practices, and adherence to safety protocols. Recognizing the human element in equipment management is essential for promoting safe and effective equipment use.

The quality of patient care is governed by the level of patient education and responsibility. When patients understand their rights, they can contribute to determining the care service they receive based on their expectations and knowledge. Well-educated patients tend to have more realistic expectations and tend to request clearly what they need from healthcare providers. Consequently, this eliminates the chances of patients repeating tests and treatments several times before it meets their expectations. For example, a diabetic patient who is educated will try to continuously control their insulin levels, reducing the likelihood of complications, hospital visits, and medical equipment use.

It is important to address privacy concerns related to data collection and use in the AI framework. From both patient and healthcare provider perspectives, ensuring the confidentiality and security of sensitive medical data is crucial. Measures should be implemented to protect patient privacy, including robust encryption protocols, access controls, and compliance with relevant data protection regulations. By proactively addressing privacy concerns, the framework can instill trust among users and promote the ethical and responsible use of AI technologies in healthcare settings.

Integrating humanfactors into the framework requires addressing several key considerations including the insights gained from understanding the needs and requirements of all relavant stakeholders. This integration helps formulate user-friendly interfaces and decision support systems, which can be integrated into the overall workflow. From the perspective of hospital administrators, key priorities include optimizing resource allocation, enhancing equipment utilization, and managing operational costs while maintaining high standards. From the perspective of biomedical engineers, effective integration demands predictive algorithms and maintenance protocols that are reliable and practical for real-world settings. When it comes to patients, factors such as prioritizing accuracy, reliability, privacy, and safety concerns are of utmost importance. Engaging stakeholders continuously through interviews, observations, and feedback mechanisms allows the framework to remain adaptive and responsive to evolving requirements. By integrating human factors into every stage of developing the framework, the AI-driven framework can effectively meet the diverse needs and concerns of all relevant parties to improve the safety and deliver quality care.

## Design Perspective

Design thinking is a human-centered approach that emphasizes understanding user needs through creativity, empathy, and iterative feedback, while systems thinking addresses the broader context by examining complex dynamics and interconnections within systems. A combination of both approaches provides a more sustainable and holistic solution to modern problems. Such integration into the AI framework for PdM in healthcare might significantly enhance system effectiveness. By focusing on user-centered design, this approach ensures that AI solutions are not only technically proficient but also align seamlessly with user needs and clinical workflows.

Figure 2A displays how data from different hospital departmental equipment is aided by an IoT approach wherein it is collected in cloud storage in real-time as in Figure 2B. Along with human factors, such as empathy and the risks associated, it is then integrated into the proposed system-based approach of Figure 2C to be monitored on the display in Figure 2D, which includes all the analytical tools. This design-integrated approach facilitates the creation of intuitive interfaces that are accessible and adaptable, supporting diverse user preferences and operational requirements. This alignment enhances user adoption and operational efficiency, ultimately leading to improved patient safety and equipment reliability. Through this method, healthcare systems can anticipate and prevent equipment failures more effectively, ensuring continuous patient care.

## System Perspective

Designing an AI framework requires prior assessment of system-related factors to optimize the performance of the system, reduce risks, and ensure efficiency and reliability. While considering system factors, multiple potential stakeholders can be directly or indirectly involved with the finalized system.[20] All personnel and departments associated with healthcare centers would be considered stakeholders in the AI framework that is developed to predict equipment failure

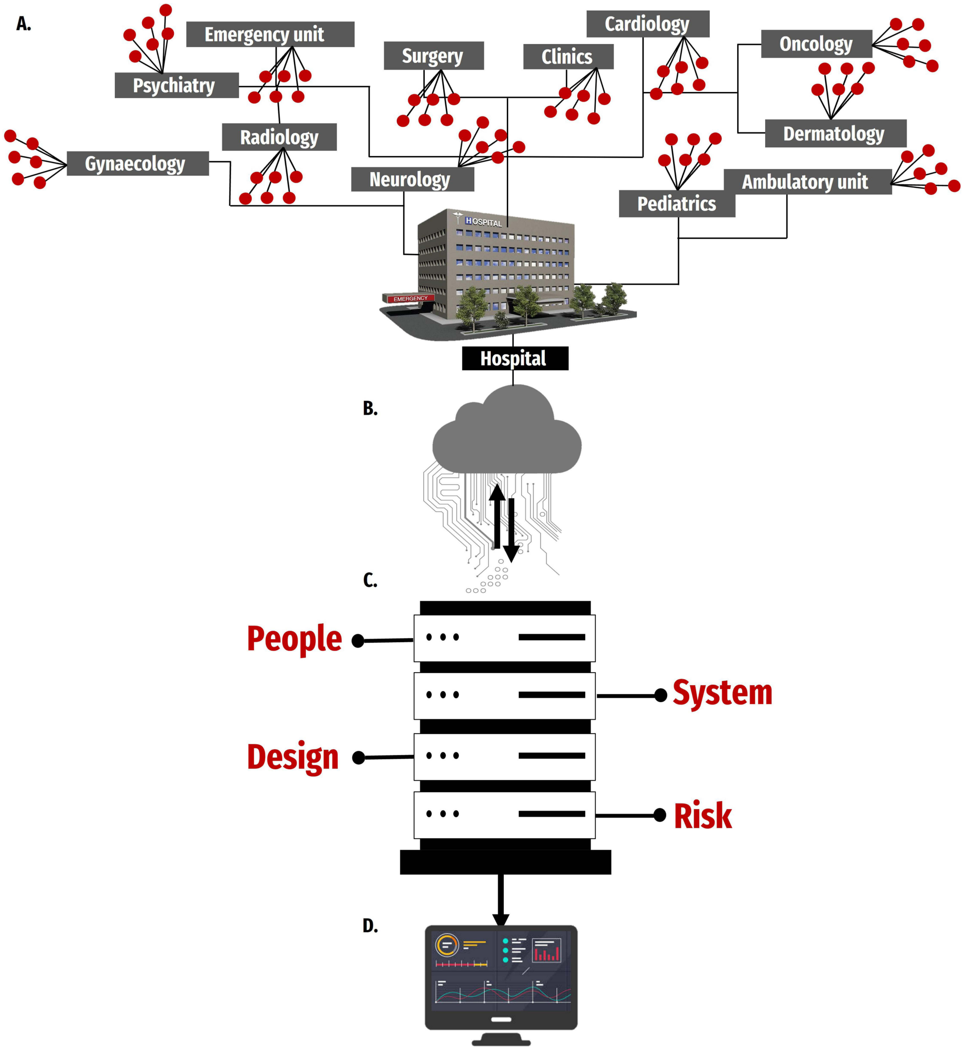


**Figure 2** Schematic illustration of the proposed AI framework for remote medical equipment management and PdM. (**A**) Each hospital department contains multiple medical equipment, represented by red circles. (**B**) Live data about the status of equipment is collected from these departments into a cloud. (**C**) Massive volumes of equipment data are fed into the proposed AI framework, which includes an analytics platform for adaptive and remote device monitoring. (**D**) Analysis of PdM and the identification of probable causes is displayed on a user-friendly interface.

in healthcare settings. Accordingly, the primary stakeholders are healthcare professionals entrusted with the critical task of utilizing medical equipment for diagnosis, treatment, and health monitoring.[23] Moreover, administration and management departments are also important stakeholders as they are concerned with hospital budgeting, operation, and resource allocation. Therefore, any initiative that can assist in facilitating improved cost management and patient outcomes will be of concern for this department.[24] Similarly, biomedical engineers and other technicians are also involved in designing the AI framework through direct interaction with equipment maintenance, optimization, calibration, and repair.[25] Other regulatory agencies and ethics experts also play an essential role in shaping the direction of any healthcare-related proposals. These regulatory bodies are responsible for validating new AI-based systems concerned with the privacy and wellbeing of individuals concerned, therefore, their interests are also essential to be considered when designing a new AI framework for early diagnosis of equipment failure.[14,26]

Similar to stakeholders, multiple elements must be considered when designing an AI framework. These elements span both the healthcare environment and technological systems, including medical equipment, sensors for data acquisition, data collection and analytics, ML algorithms for PdM models, decision support systems, integration with existing information technology (IT) infrastructure, visualization tools, and mechanisms for continuous improvement and feedback. Each of these components plays a critical role in the design of an AI-based framework for early detection of equipment failure. For instance, medical equipment is the core asset that the framework aims to support; therefore, understanding its requirements and challenges is essential for effective AI framework design.[27] Similarly, sensors for data sources will help continuously obtain required data from medical equipment, which will later be utilized by ML algorithms for continuous improvement and feedback mechanisms.[28] Moreover, the installation of visualization tools will assist in real-time assessment of equipment performance even by non-experts.[29]

Once the relevant stakeholders and key elements for the AI-based design are identified, the next step is to develop an optimal structure that ensures a seamless integration into existing healthcare frameworks. The proposed AI system should be capable of interfacing with current hospital infrastructure, allowing access to medical equipment, electronic health records, and essential parameters for assessing equipment performance. A critical component of this integration involves real-time data retrieval from medical devices, which can be achieved through the installation of sensors that directly capture performance metrics.

To enhance predictive capabilities, the collected real-time data should be combined with historical maintenance records, patient outcomes, and contextual variables such as infrastructure, population demographics, and equipment location. AI-based algorithms and predictive modeling can then analyze this comprehensive dataset to detect patterns associated with potential equipment failures. Based on these insights, AI-driven maintenance recommendations can be generated and displayed through visualization tools. To ensure effective implementation, biomedical engineers and technicians should receive training to interpret AI-generated insights and follow the suggested maintenance strategies.

Furthermore, the proposed system will operate on a continuous monitoring and feedback loop, enabling proactive equipment management. An integrated alert system can be deployed to notify healthcare personnel of potential failures, addressing the human limitation of constant system oversight. This approach not only enhances the reliability of medical equipment but also reduces downtime, ultimately improving patient safety and operational efficiency in healthcare settings.

The initial phase of implementing AI in healthcare settings involves a comprehensive understanding of the problem through detailed task analyses. The focus is on frequent equipment malfunctions, identifying common failure points and examining maintenance workflows of medical technicians and IT staff. Through these analyses, it becomes evident that AI-driven proactive maintenance can substantially reduce risks and boost equipment uptime. Roberts et al and Challen et al have demonstrated that AI analytics can provide early warnings of potential failures, thus enabling healthcare facilities to manage maintenance more effectively and avoid patient care disruptions.[30,31]

The integration of AI into equipment maintenance streamlines operations through an intuitive dashboard that delivers real-time updates, maintenance alerts, and actionable insights. This system, designed in the preliminary phase for high accessibility and ease of use, would allow both hospital technicians and administrators to effectively manage medical equipment, as highlighted by Bates et al.[32] AI systems, interconnected with existing hospital information systems, collect and process diverse data types, from operational and sensor data to maintenance logs and error codes, ensuring all data inputs are synchronized and up to date. This comprehensive interaction facilitates predictive analytics that pre-emptively identify potential equipment failures, thereby enhancing the reliability and operational efficiency of healthcare facilities. The integration of these ML models into daily healthcare operations would not only improve the user experience (UX) but also ensure that medical facilities can predict and prevent equipment failures, ultimately safeguarding patient care.

Addressing the AI product UX design is essential for ensuring system accessibility, medical standard compliance, and adaptability to diverse user preferences in healthcare settings. The system should integrate features like voice commands and high-contrast visuals, enhancing usability for various users including medical staff, technicians, and administrators, and incorporate feedback mechanisms to refine AI algorithms continuously. This iterative process is crucial for the robustness and efficacy of the PdM system going from the preliminary design to the detailed design. The dashboard allows customization and would be accessible on both mobile and desktop platforms to accommodate the diverse operational environments of users. By making these user interfaces informative and easy to navigate, the AI system ensures that healthcare professionals can efficiently manage equipment maintenance, thus enhancing patient care and operational efficiency.

Designing user interfaces for AI systems in healthcare necessitates adherence to UX principles that cater specifically to the unique demands of the sector, ensuring clarity, consistency, and accessibility. Important principles include maintaining a clear and concise presentation of information to prevent user confusion in high-stress environments, standardizing interface elements to reduce learning curves, and enhancing system accessibility for users with varying abilities. These systems should also emphasize real-time feedback to confirm user actions, error prevention for reliable operation, and customizable interfaces that adjust to individual user preferences going from the preliminary to the detailed design phase. Moreover, ensuring the security of sensitive patient data is crucial, which can be achieved through robust encryption and secure login processes. By integrating these UX design principles, AI systems in healthcare can significantly improve usability, foster wider adoption, and enhance the effectiveness of healthcare delivery, ensuring that the technology supports the complex workflows and diverse needs of its users.

The integration of AI into healthcare equipment management represents a transformative step towards enhancing operational efficiency and patient safety. AI-driven PdM systems are to be strategically designed to detect potential failures in medical equipment before they occur, significantly reducing the risk of unexpected malfunctions that can lead to severe patient care disruptions. These systems should utilize advanced analytics to provide real-time updates, maintenance alerts, and actionable insights, which are made accessible through intuitive, user-friendly dashboards. These dashboards should be tailored to ensure that both hospital technicians and administrators can efficiently utilize them, thus fostering an environment where informed decisions can be made swiftly. "Transforming healthcare with big data analytics and AI: A systematic mapping study" explores the vital role of design integration in facilitating digital transformations within healthcare systems. By implementing design thinking strategies, healthcare organizations can create more effective and user-friendly digital health solutions. This integration ensures that technological solutions are not only technically proficient but also deeply aligned with the needs and behaviors of healthcare professionals and patients. This research supports the proposition that design thinking acts as a bridge between technology and UX, optimizing the adoption and efficiency of digital healthcare innovations.[33]

The implementation of AI in medical equipment management requires a detailed understanding of the existing problems. Features such as voice commands and high-contrast visuals are incorporated to enhance usability for all users, thereby promoting broader adoption across varied healthcare settings. The robust feedback mechanisms allow for the continuous refinement of algorithms, enhancing both the robustness and efficacy of the PdM systems over time. Such advancements are crucial for evolving the capabilities of healthcare facilities to preemptively tackle equipment failures, as highlighted in recent studies.[11,34]

However, the implementation of AI technology in healthcare is accompanied by several challenges. One significant challenge is the resistance to change, which can manifest among staff members who might be skeptical of new technologies or concerned about the implications for their professional roles. To address these concerns, it is crucial to involve staff early in the planning process. This involvement can include educational sessions that demonstrate the benefits of AI, not just for the hospital's operational efficiency but also for enhancing patient care and reducing workload. Additionally, appointing proponents of AI from within the existing staff who can advocate for the changes and guide others can ease the transition. This resistance can be compounded by technical challenges, the most important one of which is ensuring seamless data integration. Other issues include maintaining system compatibility, and safeguarding patient privacy and data security. Overcoming these obstacles requires a comprehensive strategy that includes rigorous staff training, clear communication of the benefits of AI systems, and meticulous planning to ensure technical compatibility and security. Addressing these issues is essential for the successful integration of AI into existing healthcare infrastructures and workflows.

Data integration issues arise when AI systems need to communicate with multiple existing healthcare IT systems, as in Figure 2, which may operate on different platforms and use various data standards. Ensuring system compatibility often requires robust middleware solutions that can translate and convey data seamlessly between systems. Moreover, AI systems require substantial data inputs, which necessitates having a well-structured data governance policy to ensure data accuracy, availability, and privacy. To address these technical challenges, healthcare facilities should conduct thorough system audits to understand their current IT infrastructure's capabilities and limitations. Investing in scalable AI solutions that can integrate smoothly with existing technologies is crucial. Additionally, ongoing technical support must be provided to address any issues promptly.

Effective planning and execution of AI integration into healthcare requires a realistic understanding of the organization's readiness to adopt new technologies. This readiness assessment should include technical preparedness, staff willingness, and the financial and operational impacts of AI deployment. Detailed roadmaps should be developed, outlining each phase of the AI integration, from initial trials and staff training to full deployment and post-implementation review. Ensuring that all stakeholders are on board is essential for successful AI implementation.

Integrating systems thinking into medical education and healthcare technology design can revolutionize medical education by fostering a creative and problem-solving-oriented environment. The proposed framework includes system thinking which examines how different elements are interconnected and influenced by one another. For example, improving clinical training cannot be approached independently, a feedback system including educational methodologies is directly affecting the clinical decision-making, workflow efficiency, and ultimately patient outcomes. This approach is instrumental in developing new teaching methodologies that can be integrated into clinical training, thus preparing medical professionals who are adept at navigating complex healthcare scenarios with innovative solutions. There is a necessity to adopt non-linear thinking and user-centered design principles to cultivate a workforce capable of critical thinking and adaptability in clinical settings. This includes not only the medical and administrative staff but also patients, who are the ultimate end-users of any healthcare service. Transparent communication about how AI will be used, and its benefits can help in building trust and acceptance. By considering the integrated effects of AI adoption across clinical, operational, and educational layers, our proposed framework emphasizes transparent communication, trust-building, and adaptability to create an overall responsive and sustainable healthcare environment.

The adoption of AI for PdM in healthcare equipment management is a promising opportunity to enhance healthcare services' efficiency and improve patient safety. This technological integration, supported by AI's capability to analyze and predict potential equipment failures, marks a significant advancement towards more proactive healthcare management. By carefully considering user-centric design principles and addressing implementation challenges head-on, healthcare facilities can fully leverage the benefits of AI. This strategic approach not only improves the functionality and reliability of medical equipment but also sets a foundation for future technological advancements in healthcare. These advancements hold the potential to improve healthcare equipment management, making it more predictive, responsive, and aligned with the needs of modern healthcare environments. By proactively addressing both human and technical challenges, healthcare facilities can foster a more receptive environment for AI integration. This approach ensures that AI systems not only fit into the existing technological framework but also gain widespread acceptance among all stakeholders, ultimately leading to improved healthcare outcomes.

The practical implementation of AI models within healthcare systems requires a precise, multi-layered methodology to ensure accurate and clinically meaningful detection of equipment failure. This begins with a clear and context-specific definition of what constitutes "failure" for each type of medical equipment, ranging from ventilator malfunctions to faults in imaging systems. These definitions should encompass both functional anomalies and performance deviations that may compromise patient safety or disrupt clinical operations. Based on this, a discrete classification scheme can be established to distinguish between normal functioning and specific failure modes.

Effective model development also depends on robust data acquisition obtained from diverse sources such as embedded sensor logs, usage histories, and structure maintenance records. Preprocessing involves synchronizing heterogeneous data streams, filtering out noise, and extracting features indicative of failure. These data are then appropriately labeled into failure and non-failure intervals to enable reliable model training and validation. As such, model selection depends on the nature and availability of labeled data. When labels are limited or failures are rare, unsupervised or semi-supervised methods are more suitable In contrast, supervised models are ideal for large, well-annotated datasets that offer strong classification performance.

For clinical deployment, these models can be integrated into existing hospital systems such as the Computerised Maintenance Management System (CMMS). This enables real-time predictions and automated alerts. A closed-loop feedback system allows technicians to confirm or reject alerts, which can be used to retrain and improve the model over time.

While model accuracy is critical, successful deployment also requires addressing the practical challenges of real-world implementation. Ensuring compliance with healthcare data protection regulations, such as HIPAA or GDPR, is essential for safeguarding patient privacy. Moreover, not all failures are technical in nature; factors such as user error or environmental conditions can also contribute. This highlights the importance of collaboration with biomedical and clinical staff to ensure context-aware interpretation of AI-generated alerts. Streamlining these workflows will help ensure AI-based systems are both technically robust and clinically relevant.

Equally important are the broader ethical implications of integrating AI into medical equipment maintenance. These systems must be developed and deployed with a strong emphasis on safety and transparency to mitigate potential concerns. Key issues include overreliance on algorithmic outputs without sufficient human oversight, the impact of prediction errors, misalignment with clinical objectives, and the misjudgement of clinical priorities. Maintaining human involvement in decision-making is essential to ensure compliance with regulatory standards and to support more accurate validation of system performance. Incorporating these safeguards facilitates a more secure and accountable deployment process, ensuring that AI technologies enhance rather than compromise the safety, reliability, and effectiveness of healthcare delivery.

## Risk Perspective

The seamless integration of AI into the PdM systems tailored for medical equipment could transform operational efficiency and patient safety in healthcare facilities.[35] Within this framework, the primary objective is to minimize the risks associated with equipment failures, which can create serious risks, not only disrupt hospital operations, but also endangering patient care and safety. PdM systems with an AI-driven framework can accurately anticipate and prevent failures as well as ensure uninterrupted healthcare delivery. However, such advancement comes with inherent risks. Thus, it is crucial to closely examine the process, assess it firmly, and work on improving any flaws that could disrupt or hinder the correct functionality of the system.

The proposed framework relies on data harvested from hospital equipment, supported by a network of sensors intricately integrated within devices to gather specific data. The collected data then undergoes rigorous processing, training, and testing to fortify the reliability and accuracy of the framework. Regular assessment of the system is paramount to sustaining its seamless functionality and cohesive synergy. Concurrently, identifying the associated risks is essential to promptly pinpoint and rectify any system disruptions.

Integrating AI into PdM systems for healthcare equipment presents several risks and challenges that must be carefully addressed. One major concern is inaccurate predictions, as AI algorithms, despite rigorous testing and validation, may still produce false positives or false negatives. These errors could lead to unnecessary maintenance actions or, conversely, the failure to detect critical issues. Another challenge is data availability, as the effectiveness of AI models depends on consistent and comprehensive historical data, which may be lacking in certain healthcare systems. Additionally, an overreliance on AI without regular manual inspections or evaluations can create vulnerabilities, increasing the risk of undetected equipment failures. Cybersecurity risks also pose a significant threat, as AI-driven maintenance systems rely on sensitive data, including patient information and equipment telemetry.[24] Without robust security measures, these systems may be susceptible to unauthorized access and data breaches, compromising patient privacy and maintenance integrity. Lastly, ethical concerns surrounding AI decision-making in critical healthcare scenarios must be considered, particularly when human lives are at stake. Addressing these challenges requires a balanced approach that integrates AI-driven efficiencies while maintaining human oversight, data security, and ethical safeguards.

Successfully implementing and operating AI-driven maintenance systems in healthcare requires proactive measures to address the potential risks outlined earlier. By identifying and mitigating these challenges early, hospitals can minimize disruptions, enhance patient safety, and preserve critical healthcare processes. A comprehensive approach is essential, which includes continuous monitoring, strong data governance, staff training, cybersecurity, and ethical considerations. To tackle these risks effectively, several strategies should be employed. First, healthcare staff should receive comprehensive training to handle system errors and understand the limitations of the AI system. Rigorous data protection measures, such as encryption, access controls, regular audits, and staying updated on cybersecurity best practices, are crucial to safeguarding sensitive data. Establishing a support team to address emergencies related to both the AI system and the equipment is also essential. Additionally, AI model performance should be closely monitored in real-world settings, with a feedback loop that allows human experts to verify predictions, catching inaccuracies and refining algorithms. Efforts to improve data availability through enhanced data collection and quality assurance processes will ensure the effectiveness of the system. Regular manual inspections should complement AI-driven maintenance to ensure a holistic approach. Lastly, clear ethical guidelines must be established and regularly reviewed to ensure patient safety and well-being are always prioritized.

## Conclusions

This study is motivated by the growing challenges of managing medical device failures in healthcare settings, particularly in resource-constrained environments. Despite advancements in maintenance strategies, unexpected equipment failures continue to disrupt operations, compromise patient safety, and increase costs. Traditional approaches often rely on reactive or fragmented solutions, lacking a comprehensive framework that integrates technological, organizational, and human factors. AI-driven decision support systems present an opportunity to shift toward a more proactive and holistic approach, enhancing equipment reliability while aligning with the broader goals of improving patient care and operational efficiency.

To address these challenges, we propose a modified systems thinking framework that incorporates empathy as a core component. This approach ensures a holistic perspective by considering technical, operational, and human factors, enabling a structured analysis of system structures, key components, and interconnections. By facilitating well-informed decision-making at every stage, this framework supports healthcare organizations in defining, visualizing, planning, and implementing sustainable improvements in medical equipment management.

Integrating AI into healthcare equipment management presents a transformative opportunity to reduce medical device failures, enhance patient safety, and improve operational efficiency. AI-driven PdM systems enable timely interventions, optimize maintenance workflows, and minimize costs. However, realizing the full potential of AI in hospital maintenance management requires addressing existing limitations and developing innovative solutions. This study presents an AI-driven decision support framework that fills a critical gap in systematic approaches to managing medical device failures, particularly in resource-constrained settings. By leveraging AI to detect and prevent potential failures, the framework mitigates disruptions to patient care while ensuring reliability and efficiency. Additionally, incorporating human-centered design principles enhances UX by aligning AI solutions with the needs of healthcare providers and patients, promoting trust and adoption. The framework's effectiveness is further strengthened through stakeholder involvement and well-structured system design. While uncertainties such as resistance to change and technical limitations remain, proactive planning and personnel training can help mitigate these risks. Ultimately, the integration of AI into hospital equipment management represents a paradigm shift towards creating safer, more efficient, and technologically advanced healthcare environments.

The practical implementation of the proposed AI-driven decision support framework hinges on careful considerations of the type, quality, diversity, and security of the data. The proposed framework depends on the availability and integration of multi-source data inputs including structured sensor data (such as pH, temperature, pressure, and flow rate), unstructured maintenance records (such as, technician notes describing observed issues, service reports, maintenance frequency and procedures, and images of faulty components), and contextual metadata (such as usage frequency, usage patter, and environmental conditions). Integrating unstructured datasets into the framework is challenging to process but adds contextual information and richer insights that cannot be obtained from structured datasets alone. Rigorous data preprocessing and standardization must be performed on the provided datasets to exclude noisy, inconsistent, and incomplete data points that can undermine the accuracy of models. On another note, the datasets must be treated as sensitive and private content by implementing end-to-end encryption, role-based access control, and secure cloud storage practices to comply with international data protection regulations. Overall, implementing such technical and ethical regulations provides a more resilient and trustworthy framework to be adopted for practical application.

## Disclosure

The authors report no conflicts of interest in this work.

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